REPORT DOCUMENTATION PAGE

Form Approved
OMB NO. 0704-0188

Public Reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comment regarding this burden estimates or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188,) Washington, DC 20503.

1. AGENCY USE ONLY (Leave Blank)	2. REPORT DATE 1/29/02	3. REPORT TYPE AND DATES COVERED Final Technical Report

4. TITLE AND SUBTITLE
FLIR Image Classification Using Hidden Markov Trees, with Comparisons to More-Traditional Algorithms

5. FUNDING NUMBERS
DAAD19-01-1-0680

6. AUTHOR(S)
Lawrence Carin

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Duke University
Box 90291
Durham, NC 27708

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

U. S. Army Research Office
P.O. Box 12211
Research Triangle Park, NC 27709-2211

10. SPONSORING / MONITORING AGENCY REPORT NUMBER

42560-C/

11. SUPPLEMENTARY NOTES
The views, opinions and/or findings contained in this report are those of the author(s) and should not be construed as an official Department of the Army position, policy or decision, unless so designated by other documentation.

12 a. DISTRIBUTION / AVAILABILITY STATEMENT

Approved for public release; distribution unlimited.

12 b. DISTRIBUTION CODE

13. ABSTRACT (Maximum 200 words)

Signal processing algorithms are pursued for the processing of measured forward-looking infrared (FLIR) imagery. Particular algorithms explored include hidden Markov models and independent component analysis.

14. SUBJECT TERMS
FLIR, hidden Markov model, independent component analysis

15. NUMBER OF PAGES

16. PRICE CODE

17. SECURITY CLASSIFICATION OR REPORT UNCLASSIFIED	18. SECURITY CLASSIFICATION ON THIS PAGE UNCLASSIFIED	19. SECURITY CLASSIFICATION OF ABSTRACT UNCLASSIFIED	20. LIMITATION OF ABSTRACT UL

NSN 7540-01-280-5500

Standard Form 298 (Rev.2-89)
Prescribed by ANSI Std. 239-18
298-102

20021017 052

I. List of Manuscripts Submitted/Published under ARO Support

P. Bharadwaj and L. Carin, "Infrared-Image Classification Using Hidden Markov Trees," accepted for publication in *IEEE Trans. Pattern Anal. Machine Intell.*

S. Chang, B. Krishnapuram, P. Runkle, L. Carin, S. Der and N. Nasrabadi, "Feature Extraction and Support-Vector Classification of FLIR Imagery," submitted to *IEEE Trans. Image Processing*

II. Scientific Personnel

Faculty: Lawrence Carin (PI)
Post doc: Paul Runkle

III. Invention Reports

None

IV. Scientific Progress and Accomplishments

Classification of targets based on forward-looking infrared (FLIR) imagery is complicated by the fact that the associated imagery is a strong function of the target-sensor orientation (pose). Due to this nonstationarity of FLIR imagery as a function of target-sensor orientation, it is difficult to design a single classifier for a given target, and therefore we define target classes. A target class represents a set of target-sensor orientations over which the associated FLIR imagery is approximately stationary. Each target is characterized by multiple classes. Moreover, the imagery associated with a given target class can vary significantly, representative of variation in the target thermal properties. For example, the FLIR image of a target, at a *fixed* target-sensor pose can vary significantly depending on the target history (*e.g.* whether the engine is on, how long the engine has been on/off, target motion, etc.).

One of the principal challenges in processing FLIR imagery involves designating a feature vector, from which one achieves data compression. The objective is to retain as much of the discriminatory information as possible from the original image, while simultaneously reducing the degrees of freedom. In the work reported here the features are tied to particular subregions on the target, each of which ideally has distinctive thermal properties. For each such subregion a set of templates are designed, based on a Karhunen-Loeve (KL) transform

of the training data (as in a principal-components analysis). The dimensionality of the feature vector is tied to the number of subregions considered.

We investigate two techniques for designation of the subregions. In one approach the subregions are designated explicitly, based on a manual analysis of the associated FLIR imagery. The extraction of a given target subregion can be viewed as implementing a simple weighting filter: those parts of the image associated with a desired subregion are weighted by one, with the remaining portions of the imagery weighted by zero. Each subregion has an associated weighting filter. As an alternative to this manual approach, we have also designed weighting filters based on an independent-components analysis (ICA) of the available training data. This process emphasizes those portions of the FLIR image for which the associated ICA weighting filter is large, while de-emphasizing the other regions. In this case the weighting filter is no longer binary, and the number of ICA components used is analogous to the number of subregions considered in the manual approach.

Having constituted a feature vector, the classification is performed via a support vector machine (SVM), such being the subject of considerable interest recently in the classification community. An SVM is typically applied for binary classification problems, while here we are interested in classifying multiple target classes. We consider two techniques for implementing the SVM-based classification of N_c classes ($N_c > 2$). In one we build N_c SVMs, one for each class. Classifier m is used to specify a decision surface in feature space between class m and all the other N_c-1 classes. This approach has limitations, principally because the size of the associated feature vector grows linearly with N_c. We therefore also consider an alternative approach, in which we design $N_c(N_c-1)/2$ simpler SVM classifiers, for which the feature-vector dimensionality does *not* grow with increasing N_c. While the number of such SVM classifiers grows in a quadratic fashion with N_c, each associated SVM is considerably simpler than in the former approach. The performance of these two approaches is examined based on the processing of measured FLIR imagery.

V. Technology transfer

The research reported here has been executed in close coordination with the US Army Research Laboratory (Adelphi, MD). All of the research reported here has been transitioned to ARL.